Hybrid BERT vs Hybrid BERT with Hypertuning

Common Foundation:

Both reports describe a **hybrid machine learning model** that combines:

- **BERT** for contextual embedding of product descriptions.
- **LightGBM** for structured classification to predict the **week (1–8) when a product will be on discount**.
- Input features such as product descriptions, historical sale data, and price information.
- A synthetic dataset of approximately **24,575 samples** across 8 weeks.

Key Differences:

Category	**Hybrid BERT**	**Hybrid BERT with Hypertuning**
Feature Engineering	Minimal detail; limited to raw features like product description, last sale week, price changes	Extensive feature engineering: days since last sale, price diff, average cycle, is discounted
Hyperparameter Tuning	Not explicitly used; LightGBM uses default or lightly tuned parameters	**Yes — Optuna used** to optimize parameters like learning_rate, num_leaves, max_depth, min_data_in_leaf
Best Parameters	Not reported	Best trial (Trial 14): learning_rate=0.147, num_leaves=134, max_depth=6, min_data_in_leaf=47
Model Accuracy	**0.698 (69.8%)**	**0.8908 (89.1%)** — Significant improvement post tuning and feature engineering
Macro F1 Score	**0.670**	**0.7797**
Weighted F1 Score	**0.701**	**0.8903**

RMSE / MAE	**RMSE: 1.11 weeks**, **MAE: 0.52 weeks**	**RMSE: 0.5259 weeks**, **MAE: 0.1538 weeks** — Indicating better proximity to actual values
Classification Report	Summarized with macro and weighted averages	**Detailed per-class metrics** for Weeks 1 to 8, showing performance class-wise
Confusion Matrix	Basic diagonal dominance and adjacent week misclassifications	Specific callouts: high accuracy for Weeks 4–8, Week 1 misclassified due to class imbalance
Visual Analysis	Mentioned, but not supported with detailed figures or insights	**Bar chart analysis** of precision, recall, F1 per class + prediction error distribution included
Challenges & Fixes	Only recommendations	**Detailed list of encountered issues** and how each was resolved (e.g., BERT integration, LightGBM warnings)
Recommendations for Future Work	High-level: handle imbalance, try alternate models	Detailed: SMOTE, RetailBERT, class weights, real-time API, time-based CV splits, probability thresholds
Conclusion	Describes the hybrid model's strengths and general effectiveness in forecasting	**Emphasizes the enhanced accuracy, error reduction**, and readiness for real-time deployment

Summary:

Aspect	**Hybrid BERT**	**Hybrid BERT with Hypertuning**
Completeness	Moderate	High
Performance	Acceptable	Excellent
Technical Depth	Moderate	Advanced
Use of Tuning & FE	No	Yes
Evaluation	General	Granular + Visual

Recommendation:

Hybrid BERT with Hypertuning is a **significantly improved** version of the initial model, achieving:

- Better model accuracy and generalization.
- Reduced error rates (RMSE & MAE).
- Clear class-wise performance visibility.
- Robust pipeline ready for deployment or further research.